

# **Monitoring Small Area Growth with GIS: An Application to the City of Los Angeles**

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## Abstract

*This paper presents a technique of monitoring small area growth with GIS. Monitoring growth of small areas, including census tracts, blocks, or traffic analysis zones, becomes an important tool in measuring changes in small area plans (e.g., transit oriented development). Although geo-coded databases have become more popular and easily accessible in recent days, most available data is still spatially aggregated. The raster cell can be developed as a spatial base unit for monitoring small area growth. Spatially aggregated small area data is disaggregated into raster cells using land use information from both aerial photographs and local general plans. This study uses the land use weighted interpolation to develop uneven and hopefully more accurate distribution of the socioeconomic estimates within the census tract of the City of Los Angeles. This paper also discusses how to monitor the changing size and spatial distribution of small area household growth, specifically in and around the transit oriented development (TOD) areas. ArcGIS Spatial Analyst is used to implement the raster cell method.*

## 1. Introduction

Urban and regional planning requires a variety of socioeconomic data at the small area level to do detailed analysis. The socioeconomic estimates at the small area play an important role in tracing the recent trends and figuring out the likely growth pattern of the small area. Those estimates are useful to assess the effectiveness of the policy and programs, or to evaluate the accuracy of the small area growth forecasts. Small area analysis is made possible with the effective use of the geographic information system (GIS).

The small area is not defined in a definite way, but in relative way (Smith and Morrison, 2005). Demographers might treat a county as a small area, the regional scientist might treat a metropolitan region as a small area, and transportation planner might a transportation analysis zone as a small area. The U.S. Census Bureau publishes socioeconomic data for a variety of small statistical areas. Even a census block, the smallest size of U.S. Census statistical area, would be able to contain necessary socioeconomic data.

The nature of the available socioeconomic data for those small size statistical areas is spatially aggregated in a way that the socioeconomic data is difficult to be used for the very small area analysis needed. For example, we might be interested in knowing the number of housing units within a certain distance (e.g., 1/4 miles or 1/3 miles) of the transit station/corridor, the number of jobs available within 30 minutes of the residence area, the number of low income household within a certain distance of the freeway, the number of residents living within a certain distance of the hazardous toxic facility or even how these variables change over time. How do we process socioeconomic data relevant to a specific very small area?

The area interpolation method plays a key role in determining the socioeconomic estimates of the small area. Area weighting have been widely used due to its easy applicability. This method, however, might not produce the accurate socioeconomic estimates because of its “even distribution” assumption. This study uses the land use

weighted interpolation method to reflect uneven, and hopefully more accurate, distribution of the socioeconomic estimates within the small area. As a base geographical unit, the raster cell is an easily modifiable small size zone. The raster cell level socioeconomic data estimates can be easily derived because of easy access to land use image data from aerial photographs. Further, the study illustrates how socioeconomic data at the raster cell level would be used to monitor the changing size and spatial distribution of small area housing growth, particularly, in and around transit oriented development areas.

## **2. Raster Cell Methods for Small Area Estimates and Forecasts**

### **2-1. Process of developing small area growth estimates and forecasts**

The development of the small area growth forecast involves several steps (SCAG, 2007).<sup>1</sup> The following process is based on the recent growth estimates and forecast experience of the Southern California Association of Government (SCAG):

- 1) The first step starts with an analysis of recent regional growth trends and the collection of significant local general plan updates. A variety of large area estimates and projections are collected from diverse federal, state, and local data sources.
- 2) The second step involves the review and update of the existing regional growth forecast methodology and key assumptions. The widely used methodology includes the cohort-component method and the shift-share method. The key technical assumptions included updates regarding the fertility rate, mortality rate, net immigration, domestic in-migration, domestic out-migration, labor force participation rates, double jobbing rates, unemployment rates, and headship rates, etc.
- 3) The third step is to review, update and assess existing regional growth policies and strategies, including land use strategies, economic growth initiatives and goods movement strategies. Relevant analysis also includes general plan capacity analysis, application of SCAG's Compass Blueprint Program demonstration projects, regional growth principles, polling and focus groups, and public workshops.
- 4) The fourth step is to develop and evaluate the draft regional growth forecast scenarios with small area distributions. Regional growth forecast scenarios are developed and allocated into the smaller geographic levels using public workshops. The small area distributions of the regional growth are evaluated using transportation and emission modeling results and environmental impact review (EIR) reports.
- 5) The fifth and last step is to select and adopt a preferred regional growth forecast. A regional growth scenario with selected small area distributions is developed

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<sup>1</sup> ([http://scag.ca.gov/Housing/pdfs/rhna/RHNA\\_Methodology\\_rc020107.pdf](http://scag.ca.gov/Housing/pdfs/rhna/RHNA_Methodology_rc020107.pdf))

using transportation and environmental performance measures. A regional growth forecast is adopted by the SCAG Regional Council.

An organized forecasting decision making process is required to develop a consensus regional growth forecast in an efficient, open, and fair way. A variety of groups and input is involved in the forecasting process include panel of experts, subregional/local review, stakeholders/data users, public outreach, technical committee, policy committee, and the SCAG Regional Council.

Using the Southern California six county region<sup>2</sup> as an example, the household forecasts are developed at different levels of geography (see figure 1). The raster cell is currently not identified as an official geographic unit, but is being introduced for this study.

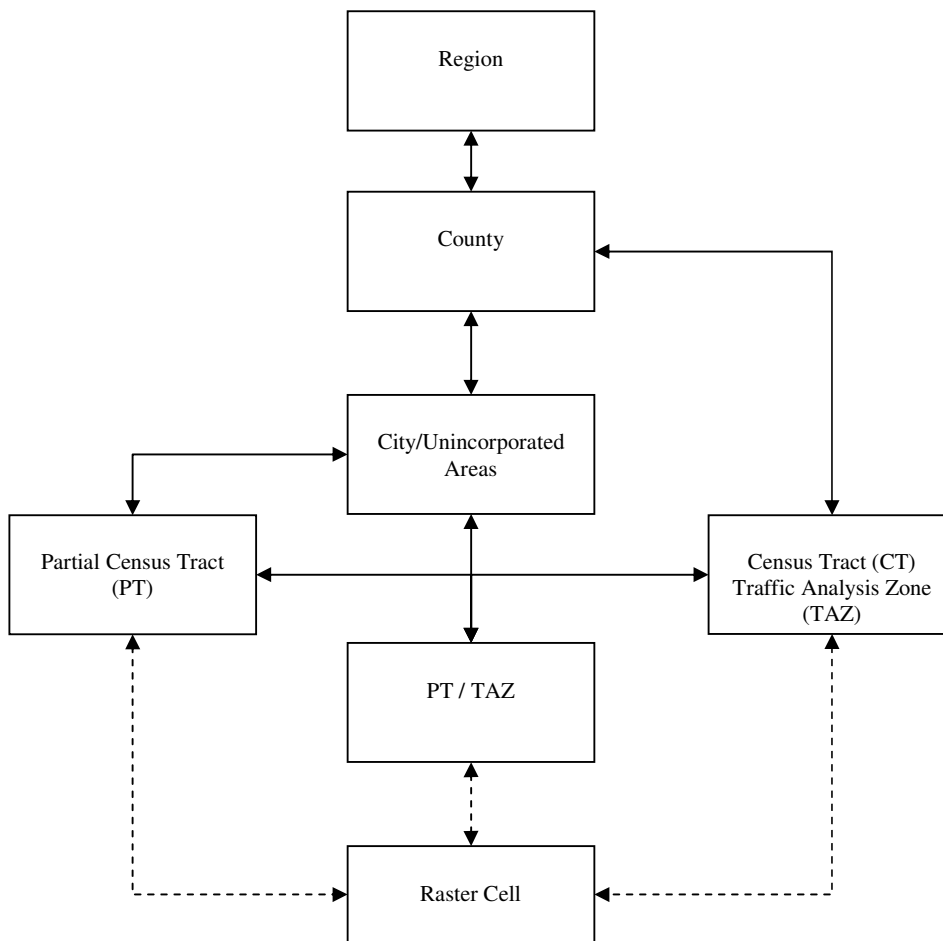


Figure 1. Different levels of geography for household forecasts

## 2-2. Raster Cell Methods

<sup>2</sup> Southern California Six County Region includes the following six counties: Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura. There are 187 cities in the 38,000 square mile region. The region's current population is 18 million or more, accounting for more than 6% of the U.S national population, and approximately half of the California population.

The spatially aggregated socioeconomic data at the census tract level can be easily disaggregated into any small size zone using the area interpolation. The GIS analysis does not require developing a raster cell as a spatial unit base. The more accurate socioeconomic information at the smaller area level (e.g., raster cell), however, is expected to inform public policy, or to support business decision making (Smith and Morrison, 2005).

GIS interpolation techniques are used to (whole or percentage) disaggregate the CT level households for buffer analysis related to TOD. Analysis of the growth within a certain distance of the station can be done using the method above.

The small area socioeconomic data of the U.S. Census can be easily summed to the large area socioeconomic data in many cases. The major problem occurs when the spatial analysis is needed for newly identified small areas, such as transportation analysis zones or neighborhood areas within a quarter mile distance of the train stations/ bus stops. Any other interpolation technique might not accurately depict the socioeconomic characteristics because of the data conversion process.

A better approach would be to use socioeconomic data of the smallest zone, which could be based on a “geo-coded” parcel (Mouden and Hubner, 2000). The tax-lot parcel becomes an important unit of land information, data collection and analysis (Enger 1992; Bollens, 1998). For example, we might be able to estimate the number of births and deaths for any different size of small area, if the birth or death data is available in a “geo-coded” parcel format. The Center for Demographic Research (CDR), California State University, Fullerton, annually estimates natural increase of the small areas of the County of Orange. Geo-coded parcel data is the ideal unit of analysis and has become more useful and popular in recent days, but such data is expensive, hardly accessible, and limited in its scope.

The tax-lot parcel contains the following land and building characteristics: acreage, land use, land value, improvement value, housing units, square footage, year built, bedrooms/bathrooms, amongst other factors. This information is conveniently available to the general public. For example, Los Angeles County Office of the Assessor developed the Property Assessment Information System (PAIS) to enhance Internet services to the public<sup>3</sup>. The PAIS internet system is composed of four major elements: the parcel display (left-side base map showing individual parcels, street center lines, city and county borders), the parcel detail (right-side property information, recent sale information, roll values, property boundary description and building description), the assessor maps, and the recent sales.

Synthetic population is sometimes produced to meet the socioeconomic data needs at the very small area level. Due to confidentiality issues, some socioeconomic characteristics at the small area are often released through the public statistics agency, but nonetheless need to be analyzed for planning purpose. Several techniques including matching method, synthetic method, Monte Carlo sampling are widely used in a variety of academic and practical fields (Clark & Holm, 1987).

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<sup>3</sup> (<http://maps.assessor.lacounty.gov/mapping/viewer.asp> accessed on April 29, 2007).

The raster cell method can be an effective method in doing small area analysis and growth monitoring because of availability of land use image data from aerial photographs<sup>4</sup>. The raster cell is used as a spatial unit base, and spatially aggregated small area socioeconomic data is disaggregated into raster cells modeling current land use image data. For example, housing units may be reasonably estimated for each raster cell by processing land use image data using ArcMap Spatial Analyst and SAS (Cho, 2006).

Landis (1997) noted that (hectare based) raster cells might have both advantages and disadvantages as units of analysis. They are small enough to capture the detailed fabric of urban land used but large enough to avoid problems of data "noise." And, since they are fixed, changes and trends across time can be easily identified. On the negative side, they lack physical or legal reality. Unlike parcels, they are not transacted. Nor are they directly regulated. Thus, they are not themselves the subject of development or redevelopment decisions<sup>5</sup>.

#### 2-2-1. Interpolation Methods

The estimates of the very small area (e.g., raster cell) are oftentimes would be very useful to perform more accurate socioeconomic analysis. Area interpolation method plays a key role in determining the socioeconomic estimates of the small area. Interpolation is defined as the method of predicting unknown values using known values of neighboring locations<sup>6</sup>. There are several interpolation methods (Cai, 2004; Reibel & Agrawal, 2006; Bourdier, 2006) described below:

##### A. Area interpolation Method

An area interpolation method was mainly discussed by MacDougall (1976) and Goodchild and Lam (1980). This method involves the following three steps<sup>7</sup>. The first step is to overlay target and source zones. The second step is to determine the proportion of each source zone that is assigned to each target zone. The third and last step is to apportion the total value of the attribute for each source zone to target zones according to the areal proportions. This method is being questioned because of its assumption of uniform density of the attribute within each zone (Cai, 2004; Reibel & Agrawal, 2006).

##### B. Intelligent Interpolation Method

As GIS and remotely-sensed satellite images become widely available, intelligent interpolation methods have been developed (Mennis, J. and Hultgren, T., 2006; Mennis, 2003, 2002; Eicher & Brewer, 2001; Fisher and Langford, 1995; Langford & Unwin, 1994; Goodchild et al, 1993). They use supplementary data such as satellite images or land use data in area interpolation to improve estimation accuracy (Sadahiro, 1999).

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<sup>4</sup> (<http://data.geocomm.com/helpdesk/general.html>).

<sup>5</sup> ([http://www.ncgia.ucsb.edu/conf/landuse97/papers/landis\\_john/paper.html](http://www.ncgia.ucsb.edu/conf/landuse97/papers/landis_john/paper.html))

<sup>6</sup> (<http://www.innovativegis.com/basis/primer/analysis.html>).

<sup>7</sup> (<http://www.geog.ubc.ca/courses/klink/gis.notes/ncgia/u41.html>).

Dasymetric map seeks to display statistical surface data by exhaustively partitioning space into zones where the zone boundaries reflect the underlying statistical surface variation. The process of dasymetric mapping is the transformation of data from a set of arbitrary source zones to a dasymetric map via the overlay of the source zones with an ancillary data set. In practice, dasymetric mapping is often considered a particular type of areal interpolation technique where source zone data are excluded from certain classes in a categorical ancillary data set. Dasymetric mapping is applicable to a wide variety of tasks where the user seeks to refine spatially aggregated data, for example in estimating local population characteristics in areas where only coarser, regional resolution census data are available<sup>8</sup>.

Mennis and Hultgren (2006) applied the dasymetric mapping to disaggregate population count at the census tract level to smaller zones. The following is how they applied the dasymetric mapping to Delaware County, Pennsylvania.<sup>9</sup> First, population data was collected from the U.S. Census Bureau for the year 2000 at the tract level, there are 148 tracts. Second, the ancillary land cover data were derived from the U.S. Geological Survey National Land Cover Data (NLCD) program. These raster data were derived from 2001 Land sat ETM+ imagery. For the dasymetric mapping, these data were smoothed using a majority filter and converted to vector format. This resulted in a vector data layer with 3,526 polygons. Third, the dasymetric mapping was applied using a 'containment' sampling method with no preset class densities and no regions. This procedure produced a new vector data layer with 4,745 polygons.

The regression modeling method is designed to estimate the dependent variables by using the estimated relationship between the independent variables and the dependent variable. Mugglin and Carlin (1999, 2000) used the regression method to include ancillary information for spatial interpolation and estimation.

Land use weighted interpolation is proposed as a way of developing the raster cell data set (Reibel & Agrawal, 2006; Cho, 2006). The interpolation can be made using the ordinary least squares (OLS) regression method or the maximum likelihood (ML) method. The regression coefficients of each residential land use category were used as weight factor for estimating population or households. Reibel & Agrawal (2006) found that land use weight interpolation improved accuracy of population estimates to some degree.

#### 2-2-2. Small Area Estimates and Forecasts

Small area estimates are different from projections or forecasts. The difference is found due to different consideration of temporal and methodological aspects (Smith et al, 2001). Population estimates are generally used by demographers to refer to approximations of population size for current or past dates while population projection refers to an approximation for a future date.

Small area estimates are developed using a wide range of data sources. Federal, state, and local governments produce a variety of socioeconomic data estimates. Private vendors sometimes fill the gap the available data and data needs. Two major agencies

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<sup>8</sup> (<http://astro.temple.edu/~jmennis/research/dasymetric/index.htm>)

<sup>9</sup> (<http://astro.temple.edu/~jmennis/research/dasymetric/dasycasestudy/dasycasestudy.htm>)

are worth mentioning. They are U.S. Census Bureau and California Department of Finance (DOF). Both U.S. Census and California DOF play a key role in producing such socioeconomic data estimates. Their estimates are important because they are widely used for budgeting purposes and a wide range of socioeconomic analysis.

Those estimates are oftentimes not enough to meet the data needs at the small area level. The small area estimates (e.g. census tract) are developed using the most recent census count (e.g., CTPP), census estimates, DOF estimates, aerial land use data, employment data from ES202, parcel level data from tax assessor's office, and building permits and demolitions. Private vendors play a major role in regularly processing and updating the data that is not available through federal and state agencies because they are not usually involved in developing the most recent update of the census tract level or below.

Small area forecasts at the raster cell level require a completely different model process than the estimation process because of much uncertainty of the future residential land use. The future residential land use of small areas is generally determined by the dynamics of housing demand and supply factors. The top down approach is most widely used. According to the top down approach, the large area's housing forecast is followed by the small area's housing forecast. This approach is useful due to its easy applicability and flexibility.

The large area housing forecast generally focuses on housing demand factors in, specifically, population projections. The methodology and assumptions of developing population projection and converting projected population into households become a key technical and policy discussion item.

The small area housing forecast and allocation process allocates of the large area's housing demands or needs into smaller areas by considering the supply factors of the small areas. The allocation methodology and assumptions play a key role in determining the future housing forecasts of the small area.

There are small area forecast models using the raster cell as a spatial unit (Smith et al, 2001; Brail et al, 2001; Waddell, 2004). The widely used models are the rule-based model. The major advantage of the rule-based model is its easy applicability and flexibility. The following is a brief overview of these rule-based forecast models.

California Urban Future Model I and II (CUF I and CUF II) are an urban growth and land use policy simulation model. CUF II, in particular, uses a raster data structure (Landis, 2001). The raster cell allocation of CUF II is primarily based on development probability (e.g., bid scores for development or redevelopment). This model was applied to the nine-county Association of Bay Area Governments region. The database included nearly 1.8 million grid-cells<sup>10</sup>.

The Urban Development Model (UDM) is an integrated land use and activity modeling system for very small areas (e.g., blocks and portions of blocks) used in the San Diego region (Smith et al, 2001). UDM is a two-stage nested allocation model. The first stage is to project small area forecasts for 208 zones using the gravity model.

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<sup>10</sup> ([http://www.ncgia.ucsb.edu/conf/landuse97/papers/landis\\_john/paper.html](http://www.ncgia.ucsb.edu/conf/landuse97/papers/landis_john/paper.html))

The second step is to further allocate 208 zone forecasts into 30,000 very small areas. The allocation is based on two factors: accessibility weight and the very small areas' capacity to accommodate growth. The average number of people for each of 30,000 very small areas is approximately 280 as of April 2000.

Subarea Allocation Model (SAM) is a small area growth forecast and allocation model for the Phoenix metropolitan area by the Maricopa Association of Governments (Walton et al). SAM is used to design and evaluate alternative land use scenarios. The subarea allocation is rule-based model and driven by the site suitability scores, which are created using measures including highway proximity, proximity to urban development, neighboring "built" uses, development probability. The current grid cell sizes are 220 feet on a size, or approximately 1.11 acres, and they can vary in size depending on the planning scale. There are approximately 2 millions grid cells<sup>11</sup>.

### 3. Data and Method

The City of Los Angeles is the largest city in the state of California and the second-largest in the United States by population. It is a global city having a population of over 4 million people as of January 1, 2007 and spanning 469.1 square miles (1214.9 square kilometers). (See figures 2 and 3)



Figure 2. The City of Los Angeles and the SCAG region

<sup>11</sup> ([www.mag.maricopa.gov/archive/PUB/GIS/Subarea Allocation Model.pdf](http://www.mag.maricopa.gov/archive/PUB/GIS/Subarea%20Allocation%20Model.pdf))

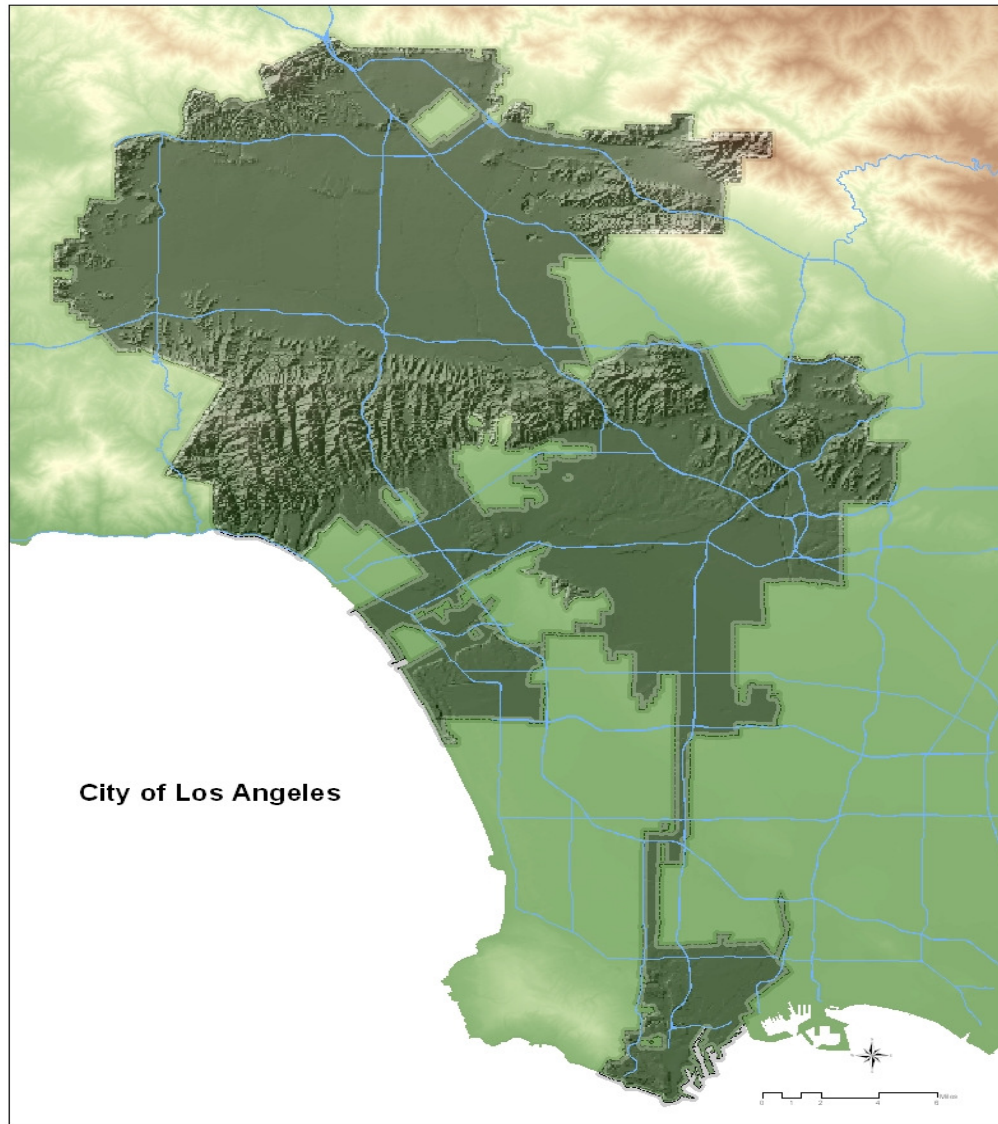


Figure 3. The City of Los Angeles

The City has added more than 1 million people and 170,000 households for more than 25 years since 1980. The household growth is much slower than its population growth. Given population growth expected in the future, the City is expected to add more than 200,000 households for the 20 year planning period.

The City currently has 837 census tracts within the city boundary as of April 1, 2000. Some census tracts cross the city boundary to include the neighboring cities or unincorporated areas. If we develop a grid cell of a 100m x 100m, the number of the grid cells would reach 48,274.

The study produces four sets of socioeconomic data at the raster cell level (100m x 100m) for further analysis, assuming that the Census Tract level data were given:

- 1) 2000 household estimates at the raster cell level (based on the 2000 Census);

- 2) 2005 household estimates at the raster cell level (based on the Claritas household estimates as of January 1, 2006);
- 3) 2005 household estimates at the raster cell level (based on 2001 Regional Transportation Plan (RTP) Household Forecasts at the Census Tract level, 1997-2025);
- 4) 2025 household forecast at the raster cell level (based on 2001 RTP Household Forecasts at the Census Tract level, 1997-2025).

### 3-1. Data

The study is based on a variety of data sources. The following is a brief overview of the data sources.

#### Aerial Photography

SCAG has acquired a set of digital ortho-rectified photography for the entire region including Mexicali, Mexico. The information was done at a 1-meter resolution for the urban portions of the region which is equal to 9,133 square miles. The additional 29,000 square miles were done at 2 meter resolution.

#### Existing Land Use

In 2000, the Southern California Association of Governments (SCAG) developed a digital land use coverage of its urban areas. The database covers the entire SCAG region, approximately 38,500 square miles, including Mexicali, Mexico.

#### General Plan

City general plans are collected by SCAG from each local jurisdiction and are stored in computerized format in SCAG's Geographic Information System (GIS). General plans are constantly being updated by the individual cities. The land use in the general plan is classified according to the Anderson (1971) land cover classification system. To make the modeling process more manageable, SCAG collapsed the 100-plus land use categories into seven: (i) undeveloped; (ii) single-family residential; (iii) multi-family residential; (iv) commercial; (v) industrial; (vi) transportation; and (vii) public.

#### Census Tract Level Household Forecasts (7/1/2000, 7/1/ 2005, and 7/1/2025)

SCAG updates the growth forecast every three or four years. SCAG Regional Council adopted a regional forecast, starting from 1997 to 2025, as part of the 2001 Regional Transportation Plan (RTP), in April 2001. The 2001 RTP growth forecast was developed in five year intervals between 2000 and 2025.

#### Claritas Tract Level Household Estimates (1/1/2006)

Claritas, a private vendor, has produced the updated demographic data every year for more than 30 years. Tract Level Estimates are developed for January 1, 2006 by incorporating many data sources. The data sources contributing to the 2006 tract level estimates are: estimates produced by local governments or planning agencies, counts of deliverable addresses from the U.S. Postal Service, household counts from the Equifax Total Source consumer database, as well as counts from the Claritas Master Address List.

#### Census Tract Level Household Estimates (4/1/2000)

The U.S. Census Bureau produces population and housing unit totals for Census 2000 at the census tract level. A census tract is a small, relatively permanent statistical subdivision of a county or statistically equivalent entity, delineated for data presentation purposes. Census tracts generally contain between 1,000 and 8,000 people<sup>12</sup>.

Residential Building Permits for the City of Los Angeles (1/1/2001-12/31/2005)  
The City of Los Angeles Planning Department keeps the recent residential building permits issued between January 1, 2000 and December 31, 2005 for single- and multiple-family housing units. This data is organized in the format of X/Y coordinates and linked to the 2000 census tract.

### 3-2. Raster Cell Household Estimates for Year 2000

Households at the raster cell level are estimated using the following equation:

$$Household_i^e = \varpi_r \alpha_k K_i$$

,where  $Household_i^e$  = household estimates of the raster cell  $i$ ,

$\varpi_r$  = a locally weighted factor for census tract  $r$  where the raster cell  $i$  belongs to,

$\alpha_k$  = estimated global coefficient for the land use  $k$ ,

$K_i$  = 1 if the land use of the raster cell  $i$  is  $k$ , otherwise 0.

The locally weighted factor ( $\varpi_r$ ) is estimated to control the total household counts of all raster cells within the census tract  $r$  for the 2000 census household counts ( $household_r$ ) of the census tract  $r$ . It can be derived using the following equation:

$$\varpi_r = \frac{household_r}{\sum_k \sum_{i \Rightarrow r} \alpha_k K_i}$$

The land use weight ( $\alpha_k$ ) is derived using the maximum likelihood (ML) method.

The census tract is used as a unit of analysis. The ordinary least squares (OLS) regression method produces a similar coefficient. The global coefficients of each land use category are used as the weight factors, and they are estimated using the following regression model.

$$household_r = \alpha_k^1 area_{1111} + \alpha_k^2 area_{1112} + \alpha_k^3 area_{1121} + \alpha_k^4 area_{1122} + \alpha_k^5 area_{1123} + \alpha_k^6 area_{1124} \\ + \alpha_k^7 area_{11125} + \alpha_k^8 area_{1131} + \alpha_k^9 area_{1132} + \alpha_k^{10} area_{1140} + \alpha_k^{11} area_{1151} + \alpha_k^{12} area_{1152}$$

where  $household_r$  is the 2000 census household counts of the census tract  $r$ ,  
a subscript with area denotes land use code, and the unit of area is 10,000 m<sup>2</sup>,

area\_1111: area of the high-density single family residential land use,

area\_1112: area of the low-density single family residential land use,

<sup>12</sup> (<http://www.census.gov/mso/www/c2000basics/00Basics.pdf>)

area\_1121: area of the mixed multi-family residential land use,  
area\_1122: area of the duplexes, triplexes, and 2 or 3 unit condominiums and townhouses land use,  
area\_1123: area of the low-rise apartments, condominiums, and townhouses land use,  
area\_1124: area of the medium-rise apartments and condominiums land use,  
area\_1125: area of the high-rise apartments and condominiums land use,  
area\_1131: area of the trailer parks and mobile home courts, high density land use,  
area\_1132: area of the mobile home courts and subdivisions, low density land use,  
area\_1140: area of the mixed residential land use,  
area\_1151: area of the rural residential, high-density land use,  
area\_1152: area of the rural residential, low-density land use.

Both the ML method and OLS method indicate that most of land uses had a statistically significant association with household estimates of the census tract ( $\alpha < 0.05$ ).  $R^2$  of the OLS is 0.8605 (adjusted  $R^2$  is 0.8601). Only one land use category (area\_1122: duplexes, triplexes, and 2 or 3 unit condominiums and townhouses) shows poor results.

The coefficient of Area\_1123 is assigned to area\_1122. This study uses ML coefficients for application.

Table 1. Estimated coefficients from an OLS regression and ML method

Variable	OLS Coefficient (t-statistics)	ML Coefficient (t-statistics)
Area_1111	8.49 (77.15*)	8.49 (77.23*)
Area_1112	0.54 (3.09*)	0.54 (3.09*)
Area_1121	54.60 (14.51**)	54.55 (14.52**)
Area_1122 <sup>a</sup>		
Area_1123	40.20 (57.67**)	40.23 (57.73**)
Area_1124	84.90 (19.07**)	84.94 (19.10**)
Area_1125	168.90 (9.37**)	168.90 (9.38**)
Area_1131	11.60 (9.44**)	11.62 (9.48**)
Area_1132	8.26 (3.02**)	8.26 (3.02**)
Area_1140	37.70 (35.71**)	37.69 (35.76**)
Area_1151	4.92 (3.75**)	5.33 (3.84**)
Area_1152	0.92 (9.13**)	0.91 (9.04**)

Source: K. Cho, Working Report, SCAG, 2006.

Note: 1) OLS good-of-fit statistics: F-statistics is 2,297.59 with 11 df;  $R^2$  is 0.8605 (adjusted  $R^2$  is 0.8601); The number of observations is 4,109;

2) ML Method good-of-fit statistics: -2 Log Likelihood is 63,801.2; AIC is 63,825.2; AICC is 63,825.3; BIC is 63,901.0; The number of observations is 4,109;

<sup>a</sup> Omitted due to a poor estimation. The coefficient value of 40.2 was assigned for the analysis.

\*\*  $p < 0.01$  \*  $p < 0.05$

The process of developing a raster cell household estimate for year 2000 is as follows:

#### A. Estimate global coefficients ( $\alpha_k$ )

- (1) Union the land use and the census tract boundary
- (2) Calculate “new area”

- (3) Summarize the new area by the census tract and by the land use category
  - (4) Merge the result of A.(3) with the 2000 census household estimates
  - (5) Convert the land use categories to households using the estimated global coefficients of the ML method.
- B. Normalize the global coefficients to control for 2000 census tract estimates ( $\varpi_r, \alpha_k$ )
- (1) Create a raster map (100m\*100m grid) for each land use category by assigning value 1 and repeat calculation for every land use category.
  - (2) Multiply the coefficient of A.(5) by the equivalent land category in the raster map above and repeat calculation for every land use category.
  - (3) Mosaic all household related maps of B.(2)
  - (4) Produce “zonal statistics” by census tract.
  - (5) Create raster maps by using the sum of B.(4)
  - (6) Create probability maps by using the map algebra (B.(2)/ B.(5)). Use the “raster calculator”.
- C. Generate Raster Maps ( $\varpi_r, \alpha_k, K_i$ )
- 1) Create a raster map (100m\*100m grid) with the census tract household data.
  - 2) Multiply B.(3) by B.(6) using the “raster calculator.”

### 3-3. Raster Cell Household Forecasts, 2005 & 2025

The household forecasts at the census tract level are allocated into the smaller raster cells using the following allocation rule. The allocation rule is developed by considering development potential.

Development potential of each raster cell within a census tract is based on the capacity of the raster to accommodate additional household growth. The additional capacity of household growth of each raster cell is based on the following four factors (see table 2): (a) current land use, (b) planned land use, (c) residential density, and (d) percent of developable land.

Table 2. The allocation priority of household growth within a census tract

Allocation Priority	Development Type	Current Land Use (a)	Planned Land Use (b)	Residential Density (c)	Percent of Developable Land (d)
A	New development	Vacant	Residential area by density	Highest of the density range for residential area by type	100%
B	Infill or redevelopment	Residential	Residential	Highest of the medium density (55 housing units per acre)	30%
C	Land use change	Industrial, commercial	Residential, industrial, commercial	Highest of the medium density (55 housing units per acre)	30%

Note: Open space and other environmentally sensitive land are excluded from additional household growth.

This study categorizes the current seven land use categories (e.g., undeveloped, single-family residential, multi-family residential, commercial, industrial, transportation, and public) into four: vacant; residential; commercial/industrial; and other land use unsuitable for development.

The future land use plan specifies both land available and land not available for urban development and redevelopment during the planning period (Berke et al, 2006). After removing areas unsuitable for residential development, each raster cell is decomposed into three major land development categories: 1) residentially developable vacant land, 2) residential infill/redevelopment, 3) industrial or commercial land. The process of allocating census tract households into raster cell is as follows (see table 2):

A. Computing the maximum household growth capacity of residentially developable vacant land: The maximum household growth capacity of residentially developable vacant land is computed by multiplying each residentially developable vacant land by maximum household density allowed in the general plan of the City of Los Angeles.

B. Computing the additional household growth capacity of infill/redevelopment land: The additional household growth capacity of infill/redevelopment land is computed by multiplying 30% of existing residential areas by maximum household density of the medium density residential areas allowed in the general plan of the City of Los Angeles.

C. Computing the additional household growth capacity of industry and office land uses: The additional household growth capacity of industry and office land uses is computed by multiplying 30% of existing industry and office area by maximum household density of the medium density residential areas allowed in the general plan of the City of Los Angeles.

#### **4. Results and Discussion**

Since small area estimates and forecasts are easily accessible at the census tract level, small area growth can be easily monitored at the census tract level. The Gini concentration ratio can be calculated to measure the degree of inequality of two distributions. (McKibben and Faust, 2004; Murdock & Ellis, 1991 & 2006). The Gini concentration ratio falls between 0 and 1. A Gini concentration ratio of 1 indicates complete inequality, with all households located in one locality. The Gini concentration ratio was calculated using household estimates and forecasts for the census tract level and five different categories of census tracts. The Gini concentration ratio ranges from 0.1902 for 2025 household forecasts to 0.2287 for 2005 household estimates. The recent housing growth pattern indicates that there is no significant change in the distribution of households between 2000 and 2005. However, two household estimates from 2000 and 2005 are more unequally distributed than that of household forecasts for 2005 and 2025 from 2001 RTP household forecasts. This implies that the 2001 RTP household forecasts for 2005 and 2025 were designed to improve the equality distribution than that of 2000 households by promoting more

growth of the census tracts with less than 1,000 households, but in reality the more equal distribution of households at the census tract level did not happen between 2000 and 2005.

Table 3. Distribution of Households by Size of Census Tract and the Gini Concentration Ratio

Households by Size of Census Tract	Number of Census Tracts as of 4/1/2000	Number of Households			
		2000*	2005**	2005***	2025***
2,501 +	79	243,247	259,824	242,984	294,209
2,001 - 2,500	84	186,545	195,962	192,927	251,293
1,501 - 2,000	187	321,853	337,224	328,604	433,444
1,001 - 1,500	307	383,233	402,496	395,585	533,615
0 - 1,000	180	141,571	147,917	152,667	222,390
All Census Tracts	837	1,276,449	1,343,423	1,312,767	1,734,951
Gini Concentration Ratio		0.2260	0.2287	0.2165	0.1902

Source: \* US Census Bureau, 2000 Census Household Estimates \*\* Claritas 2006 Household Estimates. \*\*\* SCAG, 2001 RTP Household Forecasts, April 2001.

The land use weighted interpolation method produced four sets of raster cell household estimates and forecasts for 2000, 2005, and 2025. (See Figures 4, 5, 8 and 9). The raster cell data was controlled for the census tract level data. The raster cell household growth was tabulated by three growth types (2000-2005 (actual), 2000-2005 (forecast), 2000-2025 (forecast)) and by the proximity to a transit station<sup>13</sup> (See table 4). The results indicate that the recent relative household growth within 1/3 mile of a transit station exceeds that of 2001 RTP household forecast within the same area between 2000-2005 and 2000-2025. Total estimated (actual) household growth between 2000 and 2005 within the 1/3 miles of the transit station accounts for 22.4% of total city wide estimated household growth during the same period, while total forecast household growth between 2000 and 2005 within the 1/3 mile of the transit station represents 10.1% of total city wide forecast household growth during the same period. (See Table 4, Figures 6 and 7).

Table 4. Distribution of household growth by the Proximity to a Transit Station

Proximity to a Transit Station (in mile)	2000-2005 (actual)	2000-2005 (forecast)	2000-2025 (forecast)
0-1/4 mile	12.7%	5.5%	10.0%
1/4-1/3 mile	9.7%	4.6%	7.7%
1/3-1/2 mile	18.4%	15.0%	15.9%
1/2 + mile	59.2%	74.9%	66.3%
Clustered Raster Cells	100.0%	100.0%	100.0%

<sup>13</sup> A transit station in the study would be one of 452 stations and stops (55 commuter rail stations, 122 light rail stations, and 275 rapid bus stops) in the SCAG region.

The recent pattern of relatively fast household growth within walking distance from the transit stations has two implications. The first implication is that the small area growth can be used to update the household forecasts in the coming years. More growth could be allocated into areas experiencing fast growth. The second implication is that the small area growth within walking distance of stations is attributed to strategic local and regional policies. The City's multi-pronged efforts and SCAG's Compass Blueprint Program focus growth in existing and emerging centers and along major transportation corridors. The City has implemented a transit vision strategy which has been followed by major policy shifts and infrastructure investments. At a regional level, SCAG adopted and is currently implementing the Compass Blueprint Program whose proactive approach to planning and managing growth will create the types of communities where all of us want to live work and play by providing tools and services (such as fly through simulations and economic development strategies) to cities and counties throughout Southern California to realize this growth vision on-the-ground. The use of small area growth monitoring and the raster cell method in this paper provides the opportunity to tell a story behind the possible scenarios to policy-makers of the impact that future investments and policies can impact the makeup and character of the City and the region at large.

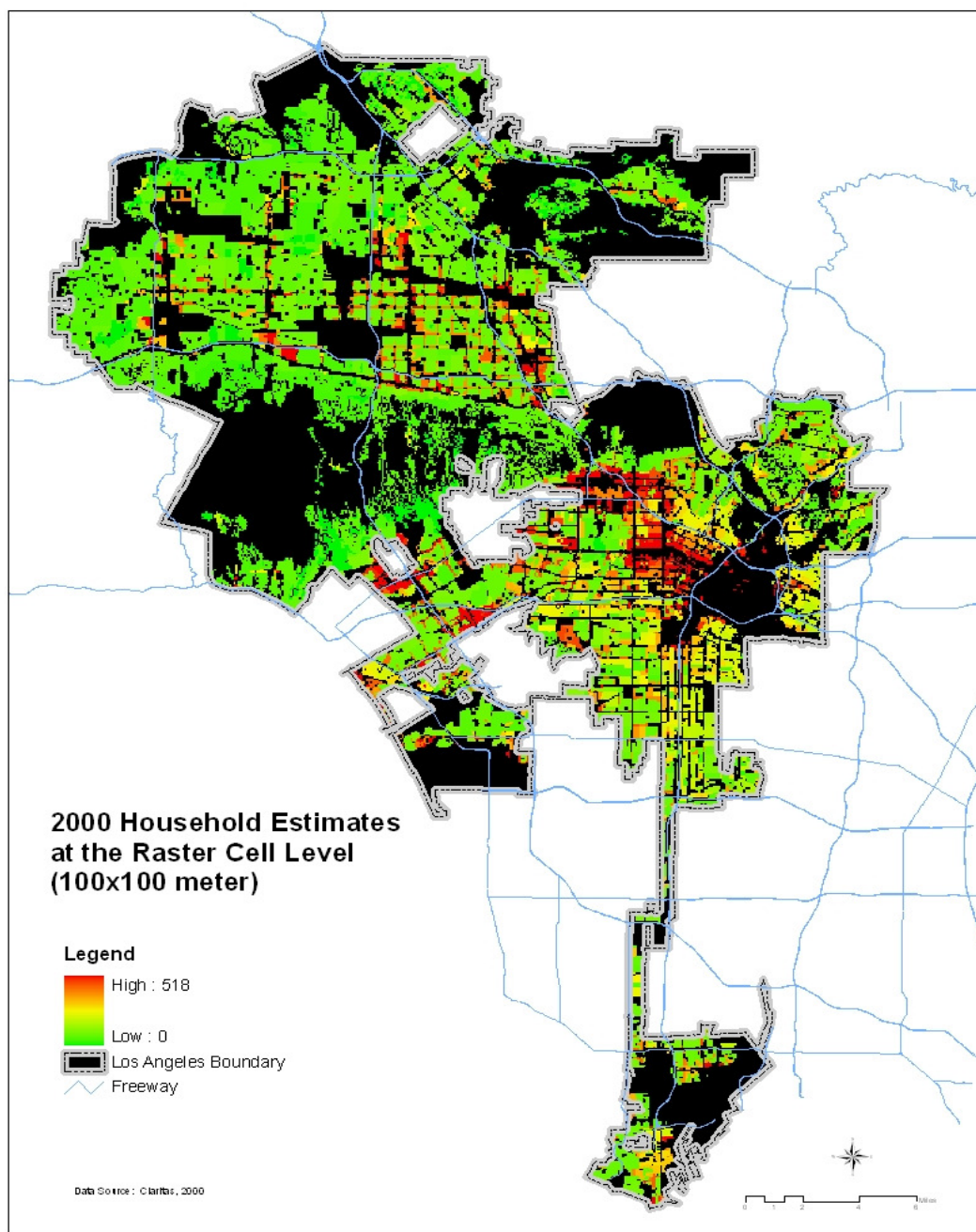


Figure 4. 2000 Household Estimates at the Raster Cell Level, 4/12000

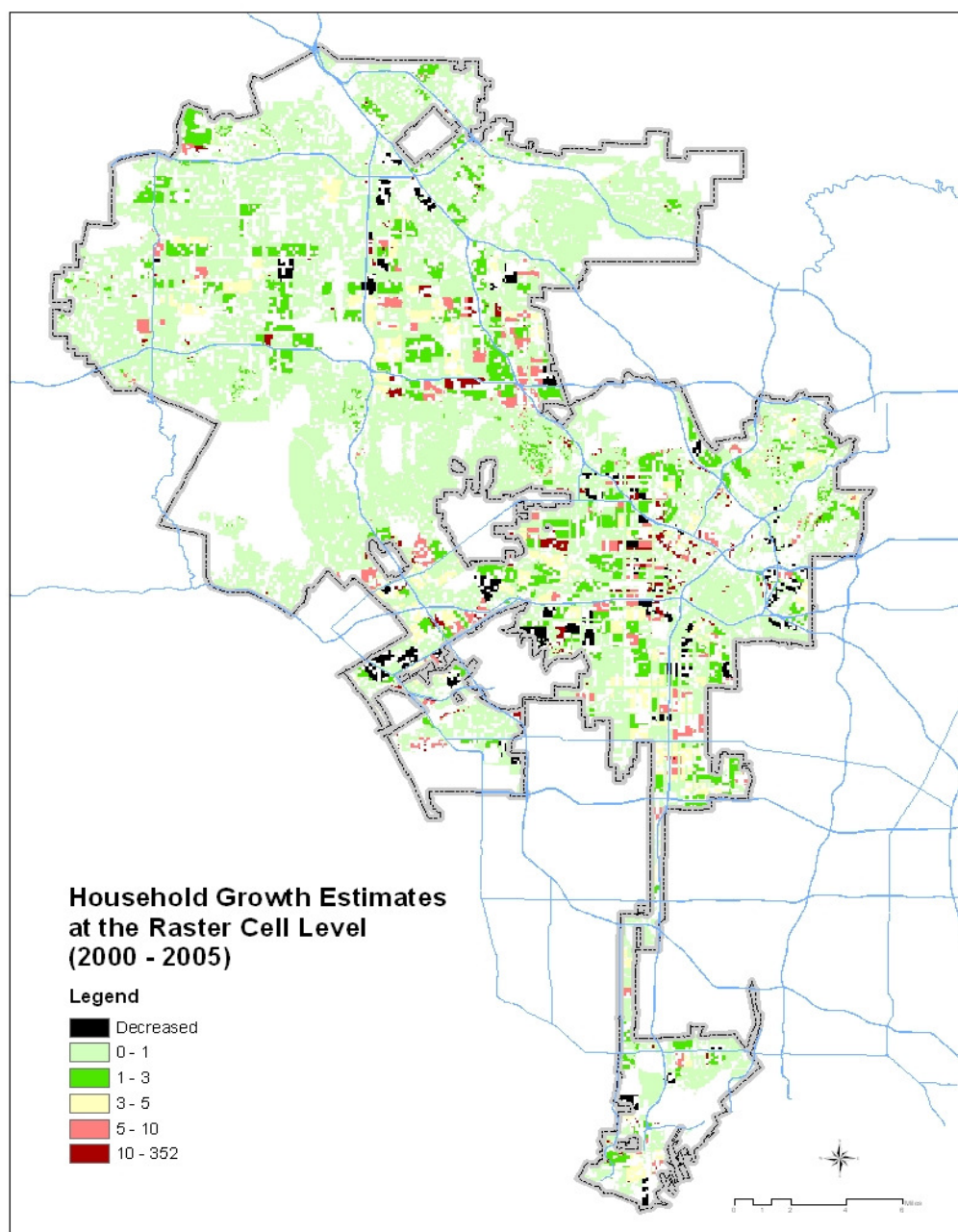


Figure 5. Household Growth Estimates at the Raster Cell Level, 4/1/2000-1/1/2006

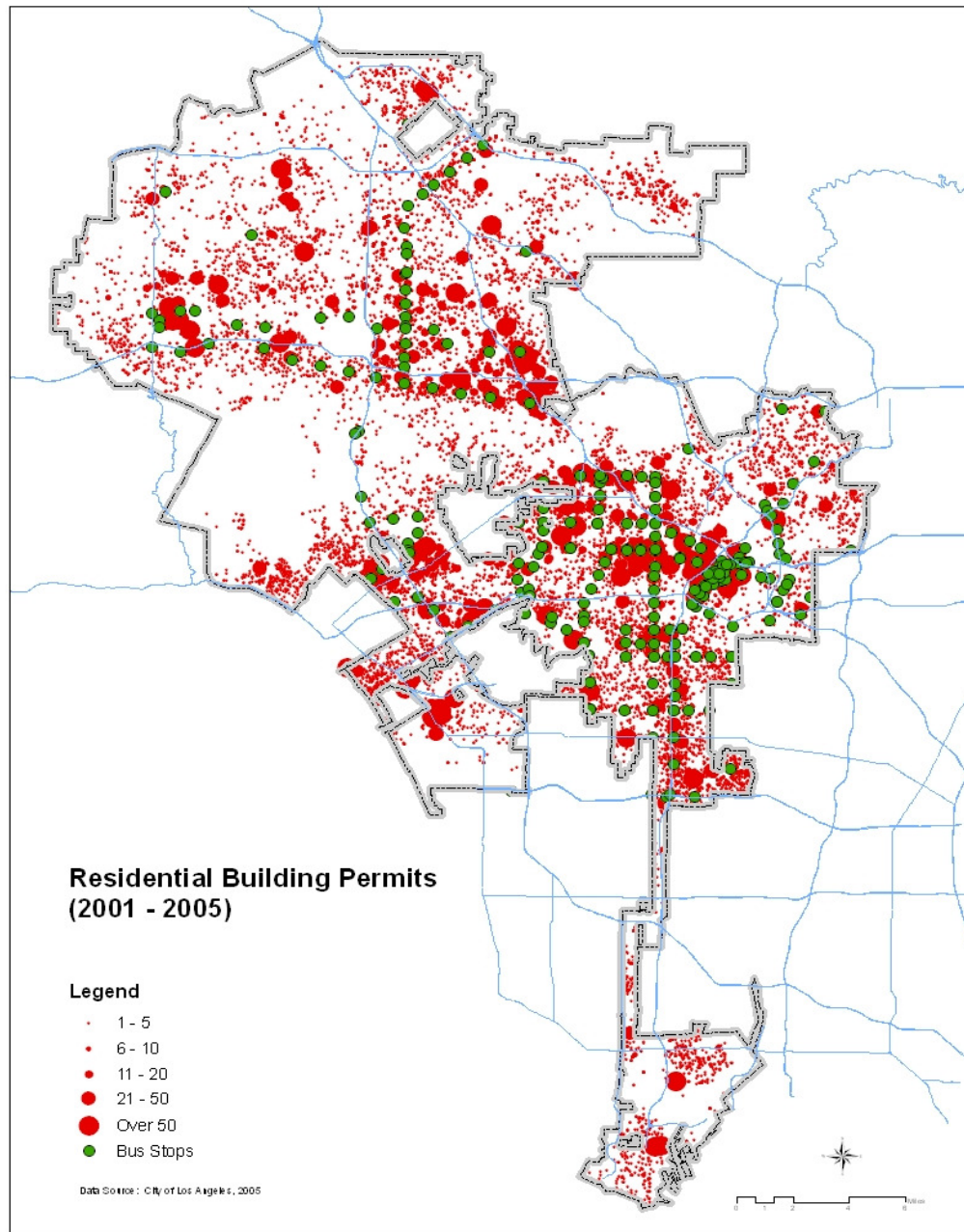


Figure 6. Transit Stations and Residential Building Permits, 1/1/2001-12/31/2005

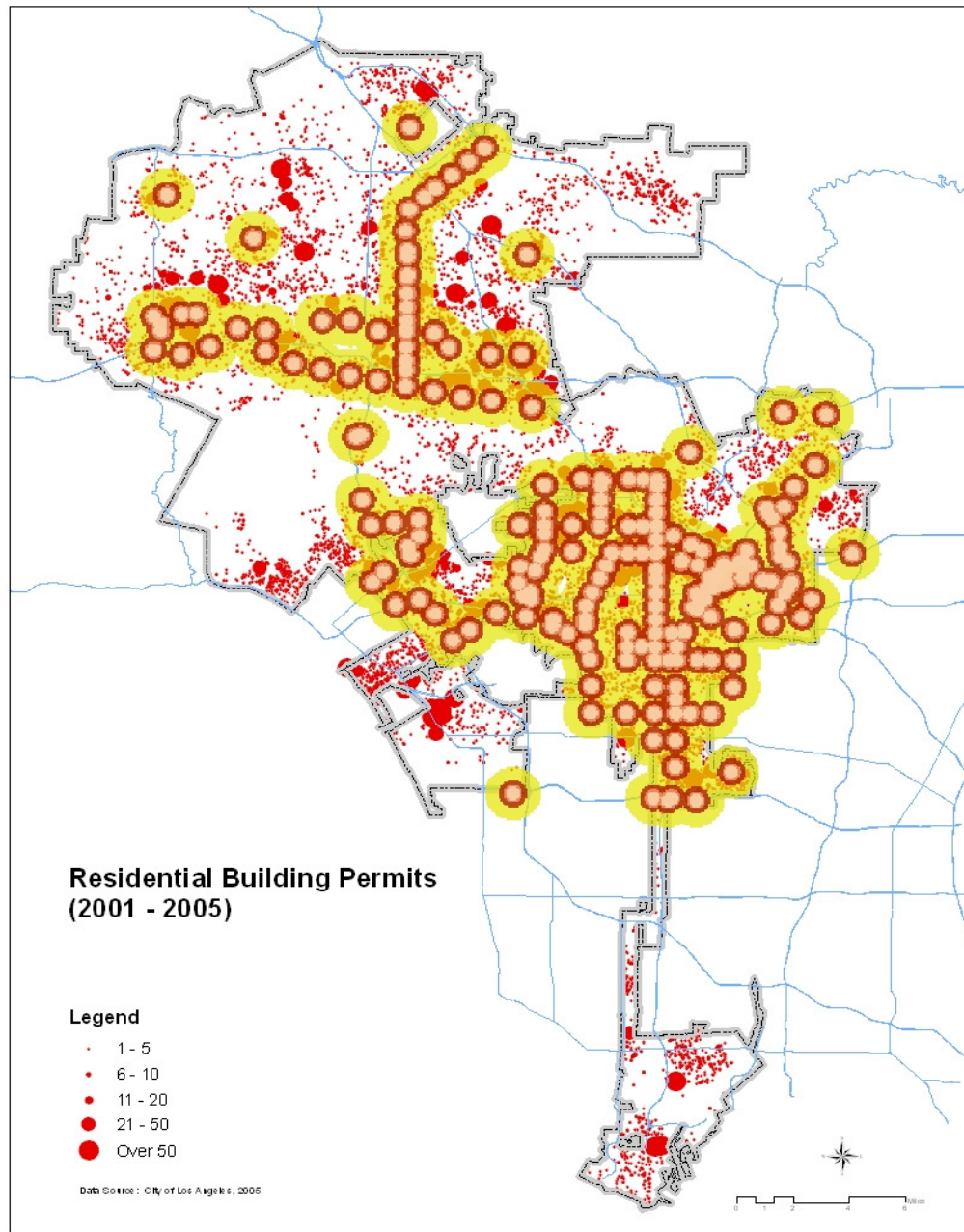


Figure 7. TOD Areas and Residential Building Permits 1/1/2001-12/31/2005

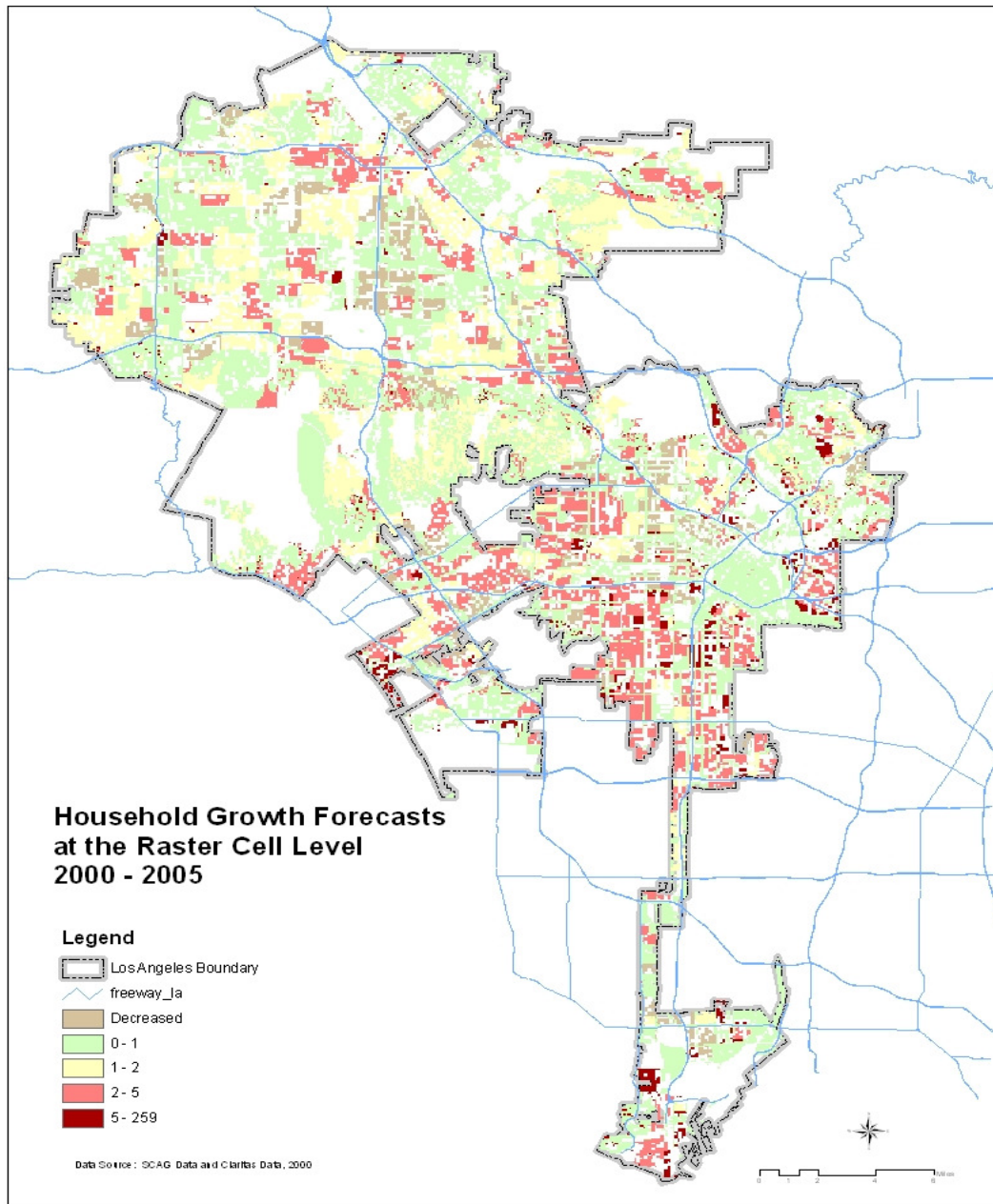


Figure 8. Household Growth Forecasts at the Raster Cell Level, 4/1/2000-7/1/2005

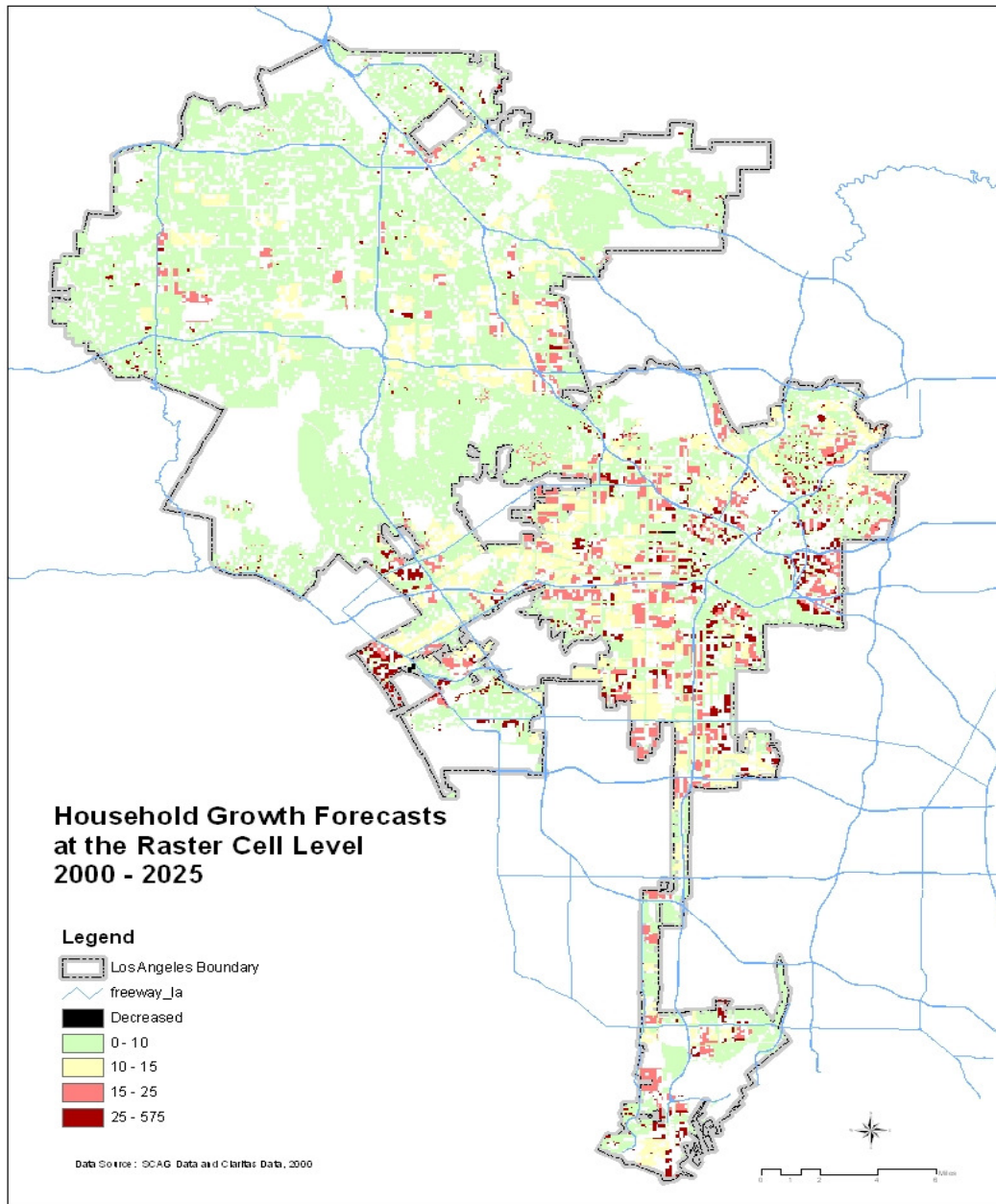


Figure 9. Household Growth Forecasts at the Raster Cell Level, 4/1/2000-7/1/2025

## 5. Conclusion

This paper presented a technique of monitoring small area growth with GIS. Monitoring growth of small areas becomes an important tool in measuring the progress of small area plans, such monitoring growth in and around transit oriented development areas. This study used the land use weighted interpolation to develop uneven and hopefully more accurate distribution of the socioeconomic estimates within the census tract of the City of Los Angeles. The raster cell level socioeconomic data estimates and forecasts were processed using land use information from both

aerial photographs and local general plans. The study also showed how socioeconomic data at the raster cell level would be used to monitor the changing size and spatial distribution of small area housing growth, in particular, around the transit oriented development (TOD) area, to be able to provide additional information to policy-makers about current and future changes that may result in the placement of policies and investments.

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